Journal of Fundamental and Applied Sciences

ISSN 1112-9867

Available online at http://www.jfas.info

Research Article

Special Issue

TRUST AWARE RECOMMENDER SYSTEM WITH DISTRUST IN DIFFERENT VIEWS OF TRUSTED USERS

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Published online: 17 October 2017

ABSTRACT

A recommender system aims to provide users with personalized online product or service recommendations to handle the online information overload problem that keep rapidly increasing. The main problems in the CF recommender system are sparsity and cold start. In order to resolve the problems, one of the current researches has been directed to the CF with a trust aware mechanism that includes trust as additional information in order to predict the rating for sparse data. This paper provides a review of the existing recommender system implementing the CF and trust aware. Furthermore, based on an empirical experiment, the

d distrust in

different views of trusted users are also reported in this paper. The results have shown that the different views have an effect on the accuracy and rating coverage of the two algorithms.

Keywords: recommender system; collaborative filtering; trust aware; distrust.

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doi: http://dx.doi.org/10.4314/jfas.v9i5s.13

1. INTRODUCTION

Since the last decades, the increasing growth of knowledge and information from the internet technology has been tremendous. With the rapid growth and wide application of the technology, the total resources of information are expanding faster than peoples' ability to process and this beneficial information is very crucial to everyone. In order to provide this useful information quickly from the huge repository of web applications, recommender systems appeared and has gained wide attention from the community for this purpose. Today, recommender systems have changed the way people find products, information and even other people.

Recommender system filter large information spaces to select the items that are likely to be more interesting and attractive to a user. Recommender systems have been beneficial and widely used in many kinds of application domain for examples online job directories, online libraries, e-commerce and social networks including Facebook and LinkedIn. Besides that, with development of e-commerce, recommender systems have been considered as important tools for sales in online stores. There are many approaches that apply different types of data and approaches in recommender systems. One of the most popular approaches is collaborative filtering that utilizing user ratings based on items. Another popular approach is content-based filtering that uses content information of items to find the match between the items and users. Additionally, demographic information such as age, gender and occupation in the user profile have also been used to recommend items to the users. More interestingly, some recommender systems combine the different approaches to improve the efficiency of the systems.

Although recommender system has been widely used, some crucial problems still remain for examples cold start and sparsity problems. Cold start problem appears due to the existence of new users or items that not received any ratings[1]. Furthermore, if the number of rating on the existing items is very small, the sparsity problem occurs. As the number of items is rapidly increasing while the users rating is progressively slow, the cold start and sparsity problems would create less rating coverage and inaccurate recommendations. In order solve the problems, a recommender system with trust aware elements have been introduced [2-3].

Trust aware recommender system is recommender systems that recommend the useful information to users based on trust. Trust is a measure of enthusiasm to believe in a user based on the competences and behavior within specific contexts in a period of time. The key property of trust aware recommender system is transitive where if a user S trusts a user T and T also trusts another user U, S will transitively trust U. In other words, S who is the active user can indirectly have a trust relationship with the recommended user (U). This situation is referred as trust propagations and contributes to the high rating coverage in the trust aware recommender system. It has been reported by many researchers that the accuracy of trust aware recommender system is better than traditional collaborative filtering approach[4].

The objectives of this paper are two-fold. First is to provide a review of the existing approaches in recommender systems including collaborative filtering and trust aware. Second is to report the results gained from the empirical experiments that have been conducted on some of the existing techniques of trust aware recommender systems.

2. BACKGROUND OF THE STUDY

2.1. Recommender System

Traditional recommender systems used several approaches to make recommendation to the users including content-based filtering, collaborative filtering and hybrid approach. Furthermore, there are also techniques that can be classified into more categories demographic filtering[5].

1) Collaborative Filtering Systems:Recommender system that utilizing this approach uses information from a group of users and their similarity with related items [6-8]. In other words, it provides recommendations to a particular user that are based upon other users' recommendations with similar interest or profiles. It takes into account the ratings provided by the related users. Collaborative filtering has been widely used in the majority e-commerce systems like Amazon[9].
2) Content-based Filtering Systems: Recommender system that utilizing this approach uses information receives from the active users and data about the items associated. It makes recommendations by comparing the user profile with the content of documents in the collection. The technique is more focus on the characteristic of the users and item rather than utilizing other data such user rating[7-8]. Without user rating requirement, the technique has an advantage in recommending more accurate contents to users[10].
3) Hybrid recommender Systems: Recommender system that utilizing this approach uses combination of many different approaches. Usually, hybrid recommender system is proposed to overcome the limitation of the existing filtering approaches. The hybrid approaches that combine content-based filtering and collaborative filtering is found to be the most common hybrid approach[7]. This is also presented in the following Table 1 that summarized the existing research with the recommender system approaches and the tested

domain. While majority of works used hybrid filtering approaches that combines collaborative and content-based filtering, demography element is also one of the interests in some of the techniques. The literature has identified that user rating and genre were the two common elements used in the demography and hybrid techniques.

Table 1. Recommender system approaches with the domain application

Study	Collaborative Filtering	Content-Based Filtering	Demographic	Hybrid
[11]	✓	✓	✓	
[12]	✓	✓	✓	
[13]			✓	
[14]	✓	✓	✓	✓
[15]	✓		✓	✓
[16]	✓		✓	
[17]	✓		✓	✓
[18]	✓	✓	✓	✓
[19]	✓		✓	
[20]	✓		✓	✓
[21]	✓	✓	✓	✓
[22]	✓		✓	
[23]	✓		✓	
[24]	✓		✓	
[25]	✓	✓		✓
[26]		✓	✓	
[27]	✓	✓		
[28]	✓	✓		✓
[29]	✓	✓		
[30]	✓	✓		✓
[31]	✓	✓		
[32]	✓	✓		

4) Demographic recommender Systems: This is a kind of recommender system that categorizes users based on their demographic or personal attributes (age, gender etc.) [33-34]. The benefit of a demographic approach is that it may not require a history of user ratings and information about an item or product compare to type needed by collaborative and content-based techniques. [35-36]. However, according to the literature, there exists

research that able to identify very little improvement of the results from the demography filtering approaches [16,37].

2.2.Trust Aware Recommender System

Trust-Aware Recommender System (TARS) is basically the consequence of traditional collaborative filtering approach. TARS considers trust link between users in order to generate recommendations[38]. Besides, many research have stated that TARS can efficiently overcome data sparsity and cold start problems which appeared in the traditional collaborative filtering approaches [2, 38-39].

In recommender systems, trust is defined based on the other users' ability to provide valuable recommendations [40].There are several properties of trust have been defined including asymmetry, transitivity dynamicity, propagation, network perspective, trust establishment and context dependency.In this paper, we focus on the network trust and trust establishment. Network trust property can be local or global while trust establishment can be explicit or implicit. The global trust network means the trust propagation involving the entire community on general agreement about the trustworthiness of a user. But in local trust, it is based on the measure of a user to another user[38]. Furthermore, for trust establishment it can be on explicit or implicit trust networks. Explicit networks are built with explicit trust statements, which are directly provided by a user for another user. While, implicit trust scores are inferred from user behavior. Table 2 presents the two trust properties of TARS.

Table 2. Network and establishment trust properties in TARS

Study	Dataset	Trust Properties			
		Network		Establishment	
		Local	Global	Explicit	Implicit
[41]	FilmTrust			✓	
[39]	FilmTrust, Flixster, Epinions			✓	
[3]	Basic Epinions dataset	✓		✓	
[42]	MovieLens	✓	✓		✓
[43]	MovieLens	✓			✓
[44]	MovieLens	✓			✓
[45]	Movie	✓			✓
[46]	MovieLens		✓		✓
[1]	MovieLen, Yahoo! Webscope				✓
[4]	Extended Epinion Dataset	✓		✓	
[47]	Basic Epinions dataset	✓		✓	
[48]	Basic Epinions dataset	✓		✓	
[49]	Basic Epinions dataset	✓		✓	
[2]	Basic Epinions dataset	✓		✓	

Based on the reviewed literature, the majority of research used local network propagation. The Table 2 also presents that the trust establishment is not depending on the trust network. However, to date, all the explicit trust establishment research used Epinions dataset. The following part, two existing techniques that used local trust network and explicit trust establishment are briefly described. The selected techniques used basic Epinions dataset in [3]and extended Epinions dataset in [4].

2.3.TARS with Network and Establishment trust properties

The techniques for TARS with network and establishment trust properties is very similar to the traditional CF. If the weight of each recommendation in traditional CF is based on the active user similarity, TARS in [3] included active user trust recommendation which is defined as in the following Equation (1).

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{k} w_{a,u}\,(r_{u,i}-\bar{r}_u)}{\sum_{u=1}^{k} w_{a,u}} \quad (1)$$

where$p_{a,i}$presents the predicted rating what active user $a$would possibly provide for item i,$\bar{r}_a$ is the average rating values given by the active user, k is the number of users who ratings the item$i$. Then, $r_{u,i}$is the rating value of user u to item i, $\bar{r}_u$ is the average of the rating values provided by user u to item i, $w_{a,u}$ is the user similarity weight of a and u as computed in the Equation (2).

$$w_{a,u} = \frac{d_{max} - d_{a,u} + 1}{d_{max}} \quad (2)$$

where$d_{max}$is the maximum allowable propagation distance (MAPD) between users of the recommender system. The value of MAPD can be preset. Then,$d_{a,u}$is the active user a trust propagation distance to the recommender u. In TARS, the trust propagation distance refers to the number of hops in the shortest trust propagation path from the truster to the trustee. As in the Equations (1) and (2) used a measure of active user a to the recommender u, the network trust property is a kind of local network. The trust values are directly provided by user u to user a, therefore the trust establishment is explicit.

Furthermore, researchers in[4] proposed new formulation of TARS that extended the basic Epinions dataset with distrust statement. The formula of calculating $w_{a,u}$ in Equation (2) has been changed as denoted in the following Equation (3).

$$w_{a,u} = T_{a,u} - d_{a,u} \quad (3)$$

The Equation (3) decreases the amount of propagated distrust from propagated trust of user against to the users that gives rating on common items i, where

$$T_{a,u} = \frac{d_{max} - d_{a,u} + 1}{d_{max}},\ D_{a,u} = \frac{dt_{max} - dt_{a,u} + 1}{d_{tmax}} \quad (4)$$

where$T_{a,u}$refers to amount of propagated trust d from user 'a' to user 'u' and$D_{a,u}$calculates the distrust values based on the propagated distrust dt from user 'a' to user 'u'.

Empirical experiments have been conducted by researchers in [3] that observed the performances of TARS with the Equation (1) on different sets of views from the Epinions dataset. The results from the experiments have shown a significant impact of the different views in relation to the different tested algorithms.

In this paper, the interest has been coined to study the performance of TARS which was introduced in paper [4] with the different views perspective adapted from[3]. Although satisfactory results have been presented in[4], the view aspects are limited to three groups of users according to the number of rating given. The analysis did not take account different views of users with both number of rating and the values of rating.

3. METHODOLOGY

In the experiments, the presented model introduced by[4] is evaluated on the extended dataset from Epinions.com. This dataset contains trust and distrust data for 132000 users, who issued 841,372 statements that include 717,667 trusts and 123,705 distrusts and 85,000 users received at least one statement. The total number of ratings is 13668319 that are linked to 1560144 numbers of different items.

The two important measures to verify the effectiveness of TARS algorithms are prediction accuracy and rating coverage[4]. The rating prediction accuracy can be measured by calculating the different (in absolute value) between the real ratings with predicted ratings. The difference is called as prediction error, which are then average overall predictions to obtain the overall Mean Absolute Error (MAE) as denoted in the following Equation (5).

$$MAE_i = \frac{\sum_{j=1}^{n_i} |ar_{ij} - r_{ij}|}{n_i} \quad (5)$$

where ar_{ij} is the real rating related to active user i and item j, and r_{ij} is the predicted corresponding rate of active user i to item j.The rating coverage of TARS is measured by using the following formula in Equation (6).

$$coverage = \frac{n_r}{n_c} \quad (6)$$

wheren_r is the total number of items that the recommender system could predict a rating for that, and n_c is the total number of items.The experiments focused on five views of trusted user as listed in the following Table 3.

Table 3. Five views of trusted users

Views	Characteristic
All users	All types of user
Cold start user	Users who gives 1-4 times ratings
Heavy user	Users who give more than 10 times ratings
Opinionated user	Users who gives 1-4 times ratings and standard deviation of rating value is more than 1.5
Flexible user	Users who give more than10 times ratings and standard deviation of rating value is more than 1.5

4. RESULTS AND DISCUSSION

The results are presented in the following Table 4. The MEA and rating coverage of the two TARS algorithms were compared according to five different views.

Table 4. Accuracy (MAE) and rating coverage measures for different TARS algorithms on different views

Mean Absolute Error, Ratings Coverage		
Views	**Algorithms**	
	TARS1[3]	**TARS2** [4]
All users	0.844, 61.8%	0.705,64.11%
Cold start users	1.099, 3.43%	**1.032, 4.52%**
Heavy users	0.862,57.47%	0.728, 77.11%
Opinionated users	1.220, 51.30%	**1.165, 58.12%**
Flexible users	0.884, 60.29%	0.738, 81.56%

In terms of MAE that presents the accuracy of algorithms, the highest accuracy of both algorithms has been produced when involving all the users. However, TARS2 algorithm that considered distrust statement seems to be able to improve the accuracy results from basic algorithm TARS1 at all views. No matters on what variation of rating values, less number of ratings from cold start and opinionated users have significantly reduced the accuracy of the algorithms. It can be seen in the table that all the MAE results from cold start and opinionated of both algorithms were bigger than the all, heavy and flexible users.

However, with variation of more than 1.5 rating values, the rating coverage can be extremely increased. As shown in the Table 4, rating coverage from cold start users is only 3.43% for TARS1 and 4.52% for TARS2. A great improvement can be seen in the rating coverage from opinionated users (51.3% for TARS1 and 58.12% for TARS2). Besides MAE, the widest coverage also generated from the flexible users.

5. CONCLUSION

Trust is the measure of enthusiasm to believe in a user based on behavior within a specific context in a period of time. In this paper, we present the important properties of trust aware recommender systems. Then, the results gained from empirical experiments that have been conducted to compare the performances of two existing algorithms with different types of view have been provided. The results have shown some improvements of using distrust statement in the TARS algorithm. In addition, the numbers of ratings together with the variation of rating values have been extremely effect the accuracy and rating coverage of the algorithms. Furthermore, the research can be extended by looking at different. For example, different views based on items rating.

6. ACKNOWLEDGEMENTS

This work financially supported byMinistry of Education Malaysia and UniversitiTeknologi MARA, Malaysia under RAGS grant scheme with number 600-RMI/RAGS 5/3 (3/2014).

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How to cite this article:
Mohamed MahtarS N A,Masrom S,OmarN, Khairudin Nand Abd Rahim S K N. Trust Aware Recommender System with Distrust in Different Views of Trusted Users. J. Fundam. Appl. Sci., 2017, *9(5S), 168-182.*